Civility and Hostility in Parliamentary Politics

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Abstract

This paper investigates whether or not a shift from majoritarianism to consensualism due to electoral reform affects the way a parliament operates. We study New Zealand's change in 1996 from single-member district system associated with single-party majority governments to a mixed-member proportional system based on coalitions. This is posited to incentivize less hostility in speeches by MPs. With an original dataset containing all speeches made by New Zealand MPs between 1987 and 2016, we use an unsupervised sentiment analysis approach. We apply a word embedding model to our data, and via seed words associated with the emotion of anger, we create a general lexicon of words anger and thus hostility. We test the validity of our methodology through different means, finding evidence that as expected, speakers/chairpersons are less hostile than MPs in general, and that speakers intervene more often in more hostile debates. We find substantial evidence suggesting that, in general, the New Zealand parliament has become more collegial and consensual over time. We find weaker but suggestive evidence that the 1996 reform decreased hostility, particularly hostility in the upper percentiles, and that this was an institutional change, affecting the behavior of existing and newly elected MPs.

JEL Classification Numbers: D72, H10.

Keywords: Civility, Hostility, Parliamentary Politics, Natural Language Processing, Word Embedding.

1 Introduction

This paper investigates whether or not a shift from majoritarianism to consensualism affects the way a parliament operates. Specifically, we focus on the case of New Zealand, where a binding national referendum in 1993 changed its single-member district with a first-past-the-post system to a mixed-member proportional (MMP) system in the subsequent 1996

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election. The new system was inspired by the proportional representation system used in Germany and substantially changed New Zealand's politics. Before the reform, New Zealand had arguably the purest example of majoritarian politics, in which the two major parties, Labour and National, duopolized the parliament. Either party always formed single-party governments and winner-takes-all politics was the norm. After the reform and the rise of multi-partyism, no party is now able to form a single-party majority government. As a result, minority governments have to negotiate policy terms with the opposition. Thus the case of New Zealand is ideal for this study.

In answering our research question, we employ a novel approach in text analysis to analyze an original data set on all the speeches made by members of the New Zealand parliament between 1987 and 2016. Following Hatzivassiloglou and McKeown (1997), Turney (2002), Turney and Littman (2003), and Rheault et al. (2016), we use an unsupervised sentiment analysis approach to classify speeches. In doing so, we apply a word embedding model with seed words to create our own lexicon. In contrast to the existing literature on a similar topic (Rheault et al. 2016; Rudkowsky et al. 2018), which classifies speeches to positive and negative ones, we measure the emotion of anger. We make the use of a large-scale crowd-sourced data set called Emolex (Mohammad and Turney 2010; 2013), which classifies words as associated with emotions, in particular anger, as the seeds. We employ several approaches to find concurring evidence suggesting our methods are valid.

With this novel data set on anger, we look at overall trends before and after the electoral reform and run statistical tests and regression models. Our findings suggest that in general the New Zealand parliament has become collegial and consensual over time. The decrease in hostile speeches appears to have been driven by the changing behavior of ruling party members, whether they are from Labour or National. The reform, in particular, seems to have lowered peak hostility by MPs, where peak hostility is hostility in the upper 90 and 95 percentiles. These findings are consistent with the view that in a consensual democracy, the parliament is an arena where parties engage in deliberations and negotiations, as opposed to majoritarianism and adversarialism.

As the first paper to use the word embedding model to detect and measure the emotion of anger inside parliament, this paper contributes to several streams of the existing literature. First, it contributes to the literature on electoral reform. Democracies can be broadly categorized into majoritarian and consensual models (Lijphart 1999) and the electoral reform in New Zealand was expected to correct some systemic failures of majoritarianism, such as governments representing significantly less than a majority of the voters (Shugart 2001). Although some scholars are skeptical about the effects of electoral reform (e.g. Barker and McLeay 2000; Levine 2004), the effects appear to have had some impact on moderating adversarialism inside the New Zealand parliament. Second, it is related to the emergent literature on text analysis in political science and social science in general. The increasing number of scholars analyze parliamentary speeches to investigate the issues of polarization (Gentzkow et al. 2017), personalities (Ramey et al. Forthcoming), and democratization and suffrage expansion (Spirling 2016). Meanwhile, the recent developments in machine learning and deep learning now allow for the more fine-tuned sentiment analysis and opinion mining (Liu 2015; Pennington 2014). As far as we know, only Rheault et al. (2016) and Rudkowsky et al. (2018) have been able to fully utilize these recent developments in political science, broadly defined.

This paper is structured as follows. The next section describes the historical background of the electoral reform in New Zealand. Section 3 will introduce our methodology about data collection, word embeddings, and assignments of anger scores to words and sentences. Section 4 will look at the overall trends in the hostility inside the New Zealand parliament and conduct some simple tests and regression analyses. Section 5 concludes.

2 Historical Background

New Zealand before 1993 was a typical majoritarian democracy. According to Lijphart (1999), a majoritarian model of democracy should feature concentration of executive power in single-party majority cabinets, executive dominance, a two-party system, and a majoritarian and disproportional electoral system, among others. New Zealand had these features until 1993. Between 1935 and 1993, all the governments were single-party majority governments formed by either of the two major parties, Labour and National. The electoral system used had been single-member plurality. Thus Lijphart (1987) put it before the reform: "New Zealand has a special status among the world's democracies as the purest example of the Westminster model of government" (p.97).

The electoral system's failures became apparent by the 1980s (Shugart 2001; 2008). First, the two major parties did not offer the voter with a choice of clear alternatives. As documented in detail in Lewis et al. (1996), for example, a series of liberalization policy reforms were implemented in the 1980s by the Labour government, traditionally a social democratic party with its primary constituents being trade unions and the poor working class. This suggests the distinction between the policies of the Labour and National parties had significantly fallen. Second, the single-member plurality system created governments representing significantly less than a majority of the voters. None of the governments formed between 1954 and 1993 won a majority of the votes in the elections. Sometimes plurality vote winners were not equal to plurality seat winners, as in 1978 and 1981. Like UKIP in the 2015 election in the UK, it was not uncommon that third parties winning more than ten percent of the votes, such as Social Credit, won not more than one or two seats.

As a consequence of this, the Labour government organized the Royal Commission on the Electoral System in 1984 to correct the majoritarian bias in the existing system. Published in 1986, the RCES's (1986) report called for reform to a mixed-member proportional system as used in West Germany at that time, emphasizing fairer distribution of seats to minor parties, more diversity in representatives, and more effective representation of minority groups, especially Maori. As summarized by Lijphart (1987), the reform "would weaken the two-party system, increase the chances that partisan issues other than socioeconomic ones would emerge, make coalition or minority cabinets likely, and, as a further result, decrease the dominant power of the cabinet vis-vis parliament" (p.98). A binding referendum concurrently held with the 1993 election saw a majority of the voters reject the existing system and prefer a change to MMP.

The new MMP system is fundamentally a proportional representation system, since parties' seat shares in the 120-member parliament are ultimately determined by their vote shares on the list component. Thus one of the greatest changes to the New Zealand parliament is the birth of several new parties. As shown in Figure 1, the effective number of parties

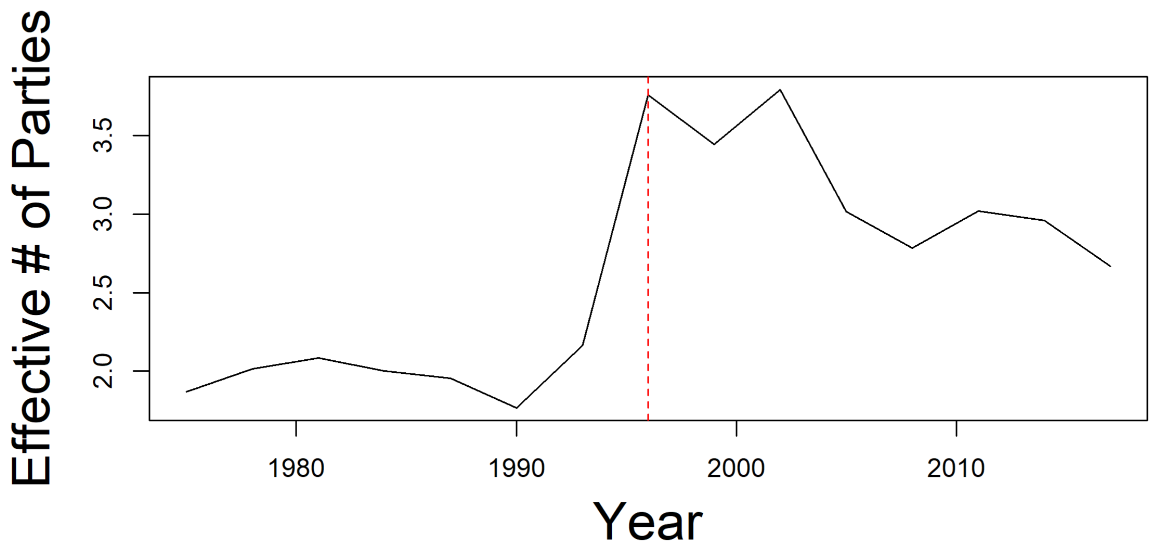


Figure 1: Effective Number of Parties in the New Zealand Parliament, 1974-2017.
Note: The red dash line indicates the year of the first MMP election.

rapidly increased from 2.16 in 1993 to 3.76 in 1996, the year when the first MMP election was conducted. In addition to the two major parties, small parties, such as New Zealand First, Green, United, ACT, Maori, and others, also win substantial portions of seats in the elections.

One of the consequences of the rise of multipartyism in New Zealand is that now it is very difficult for a single party to win a majority of seats in the house. From 1996 on, no party obtained a single-party majority. Except a coalition government formed by National and New Zealand First in 1996, all the governments formed were minority governments with confidence and supply support from small parties. Thus governments under the new system are obliged to abandon winner-take-all politics in governing and forge policy agreements with other parties in the parliament. As Malone (2008) observes, post-reform governments have to modify their bills more often than in the past to accommodate policy demands from small parties.

This institutional and systemic change leads to the theoretical expectation that the New Zealand parliament should be more collegial and consensual than in the past. That is to say, with the need to form coalitions, parties have a potential incentive to tone down their language and rhetoric inside the parliament debates. We believe there are several different possibilities as to why this might happen. Firstly, the necessity of creating coalitions means that employing harsher language towards other parties may potentially make it harder for politicians to justify future coalitions to their voters, as outright hostility can create a perception of other parties being "the enemy." Another possibility is that once in a coalition, past hostility may potentially make it harder for politicians of different parties to create an effective working relationship, incentivizing a reduction in hostility, especially with potential partners.

We propose two different ways to empirically test this general proposition that MPs should tone down their language because of new concerns about coalitions. The first straightforward way is to compare the levels of verbal aggressiveness inside the New Zealand parliament before and after the electoral reform. The second way focuses on whom MPs speak to: MPs should strategically tone down their language when they speak to future coalition partners. To put it differently, given that the minority government has been almost always the norm after the reform, small parties now have strategic leverage to pressure the government to enact their pet policy. Thus when a speech is directed towards a small party member, its tone should tend to be less hostile, especially when the speech is made by a ruling party MP.

There are no commonly agreed-upon views about these hypotheses in the literature on New Zealand politics. Some analysts, observing how the parliament worked in the first few years under MMP, stated that the reform did not necessarily transform the nature of parliamentary debate and that majoritarianism and adversarialism remained dominant in the parliament (Barker and McLeay 2000: p.143; Levine 2004: p.658). Meanwhile, others suggest that changes have been taking place in line with the hypotheses of this paper. Palmer and Palmer (2004) argue that "MMP has slowed down the system of government; made it less friendly to executive power; increased the distinction between the Executive and Parliament; revitalised Parliament" (p.13). Based on interviews with party leaders, Lundberg (2013) concludes that "New Zealand developed a unique pattern of minority government, resembling something more like a diluted form of the Westminster model with its bipolar party system, a slight movement away from the majoritarian model" (p.623). Williams (2012) uses final votes on bills between 1987 and 2007 to find that the level of consensus significantly increased and Labour and National occasionally collaborated on bills after the introduction of MMP. We thus hope that this paper helps towards answering this question, of the effects that this voting reform had on the parliamentary system of New Zealand.

In sum, once "the purest example of the Westminster model of government," New Zealand changed its electoral system from single-member plurality to MMP. The result has been the rise of multipartyism and minority governments, requiring the government to collaborate more with opposition parties. Thus we expect the parliament to become more collegial and consensual, which should be captured by less hostile debates inside the parliament.

3 Methodology

Our aim is to classify speeches made by MPs inside the parliament. Of various ways to do so, we choose to use the lexicon-based unsupervised classification method as introduced by Hatzivassiloglou and McKeown (1997), Turney (2002), and Turney and Littman (2003). Rheault et al. (2016) apply a similar method to British parliament data, using a sentiment analysis approach of positive and negative, while our approach focuses on the emotion of anger to identify hostile speeches in the parliament debates.

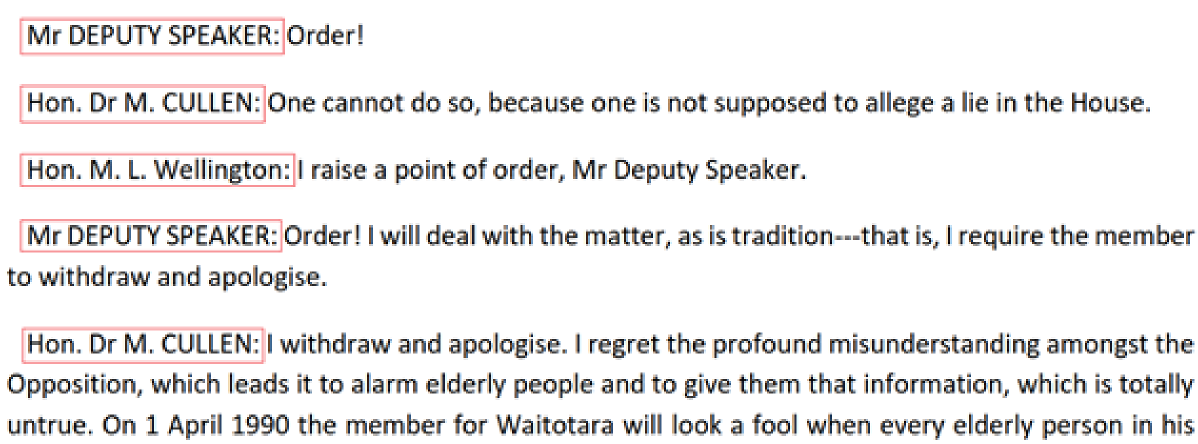
3.1 Data Collection: Raw Text Data from Hansard

In order to systematically test the hypotheses above, we collect speeches made by members of the New Zealand parliament before and after the reform. Speeches are recorded in

Parliamentary Debates (Hansard). The New Zealand Parliament websites hosts historical Hansard as digitized files in the PDF format from 1854 online.[1] We focus on the period between September 16, 1987 (the very beginning of the 42nd Parliament) and June 9, 2016 (the middle of the 51st Parliament) The observation starts from the 42nd Parliament, because the optical character recognition quality of the files for the period prior to 1987 is, unfortunately, too low to be reliably used. In addition, there are missing pages in the digitized historical Hansard files in the same period, probably because of scanning errors. We end the observation on June 9, 2016, because Hansard for the period after this day is not available as the same PDF format.

Each volume of Hansard is a 700- to 1,000-page document that contains given topics on the agenda on a given day. Topics range from debates over bills, questions and answers, and statements by the Speaker of the House and the Prime Minister, to any ceremonial and procedural events like final voting on a bill that took place in the parliament in a given period. For example, topics on May 28, 1991 included: "Weekly Statement," "Select Committees Sittings," "Questions for Oral Answer," "Inquiry into the Civil Aviation Regulations 1953," and "Appropriation Bill (No. 3)." These classifications are provided by the Hansard. During the period that we cover, the average parliamentary meeting discusses 9.5 topics on a single day, with the standard deviation of 6.1. The period that one volume of Hansard covers ranges from only one day to more than three months, with the average being 27.8 days. In total, we cover 232 volumes of Hansard and 21,032 topics discussed on 2,203 parliamentary meetings.

Of these topics found in Hansard, we focus on any types of speeches whose speakers can be identified. As shown in Figure 2, Hansard records an MP's speech with his or her name (or "SPEAKER" when a speaker is the Speaker of the House) followed by a colon (":"). With our coding, we are able to identify 821,442 speeches made by MPs in the observed period.



Mr DEPUTY SPEAKER: Order!

Hon. Dr M. CULLEN: One cannot do so, because one is not supposed to allege a lie in the House.

Hon. M. L. Wellington: I raise a point of order, Mr Deputy Speaker.

Mr DEPUTY SPEAKER: Order! I will deal with the matter, as is tradition---that is, I require the member to withdraw and apologise.

Hon. Dr M. CULLEN: I withdraw and apologise. I regret the profound misunderstanding amongst the Opposition, which leads it to alarm elderly people and to give them that information, which is totally untrue. On 1 April 1990 the member for Waitotara will look a fool when every elderly person in his

Figure 2: An Excerpt from Hansard Volume 500, p.67.
APPROPRIATION BILL (No. 4), August 8, 1989.

The next task is to lemmatize and tokenize each speech into a chunk of words. We use

[1]https://www.parliament.nz/en/pb/hansard-debates/historical-hansard/

TreeTagger, a part-of-speech tagger (Schmid 1994; 1995) to reduce words to their root forms, so that inflected forms of a given word – such as "argue," "arguing," and "argued" – can be grouped as a single item, or "argue." Meanwhile, we do not remove stop words, or short functional words that appear in documents very frequently, such as "a," "about," "above," "after," and "again," because these words can have some meanings depending on a given context. In addition, we do not stem words, meaning that "argue" and "argument" are treated as different words. As is discussed in Denny and Spirling (2018), this falls within the range of normal pre-processing done for natural language processing.

This preprocessing results in 134,643 unique broadly defined words in our corpus. The average length of a speech is 155.9 words with the standard deviation of 316.5. The average lengths of speeches, aggregated at the monthly level, are shown in Figure 3. Speeches have become longer towards the end of the observation period.

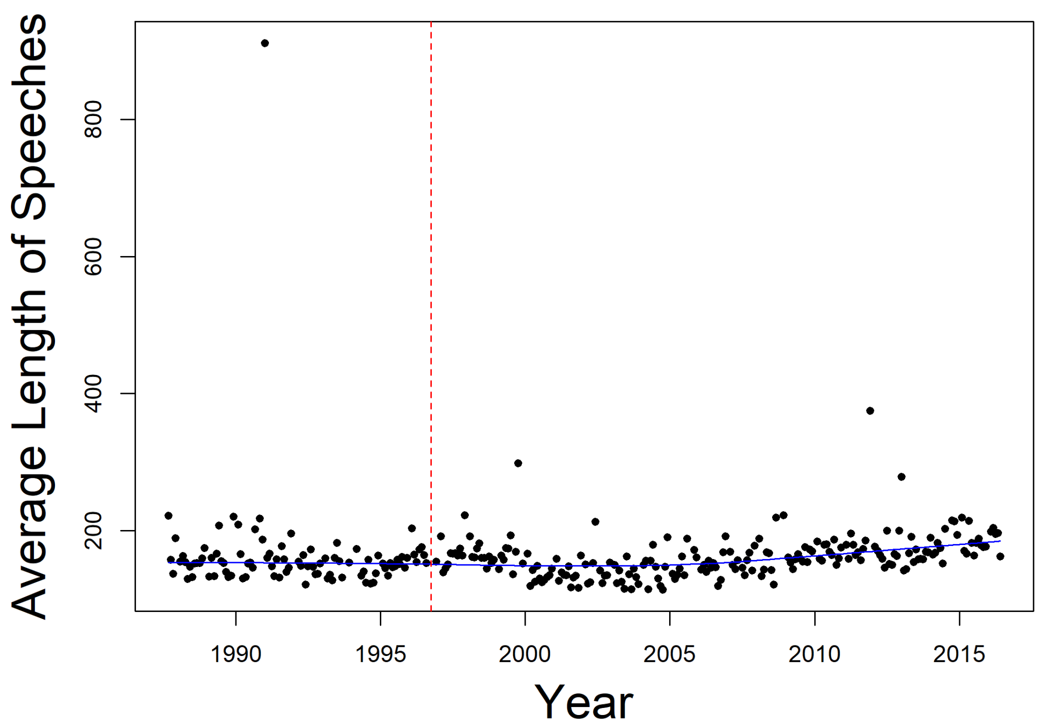


Figure 3: Average Length of Speeches Made by MPs.
Note: The red dash line indicates the year of the first MMP election.
The blue solid line indicates the lowess curve.

3.2 Word Embeddings Using GloVe

There are various ways to create a lexicon of sentiment words. One can use some existing lexicons such as the General Inquirer and WordNet. We instead use the broad approach seen in papers such as Hatzivassiloglou and McKeown (1997), Turney (2002), and Turney and Littman (2003): that is, to calculate the proximity between words that appear in a given text. Word-to-word proximity can be calculated by using cosine similarity of words represented as vectors, or formally,

$$cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum\limits_{i=1}^{n} A_i B_i}{\sqrt{\sum\limits_{i=1}^{n} A_i^2} \sqrt{\sum\limits_{i=1}^{n} B_i^2}}$$

where $A_i (i = 1, ..., n)$ are components of a n-dimensional vector $\mathbf{A}$ for a word. As described in the next subsection, with word-to-word proximity scores and seed words, it is possible to estimate sentiment scores for words and, in turn, sentences and paragraphs.

The approach thus requires vectorization of words that appear in the corpus. Even after our pre-processing, our corpus size of 134,643 unique broadly defined words is quite large, so to aid in computing times, we restrict our corpus further by creating a vector space of 36,726 words that appeared at least ten times across the observation period. As a robustness check, we also conduct some of our analyses using all 130,000+ words and do not find significant changes.

We then make use of the Global Vectors for Word Representation method, or GloVe (Pennington et al. 2014). The advantage of using such a method, as opposed to a simple dictionary approach, is that word embeddings allows for the meaning of a word to be associated with the distribution of words surrounding the word. For example, even when we do not know the exact meaning of a word "ice," still it is possible to guess the meaning of the word by investigating its associations with other words that are likely to co-occur in a given local context, such as "solid" and "water." We set a local context window as 30 words, or 15 words before and after a given word. A vector length is set at 300.

GloVe estimates word vectors that will minimize the loss in the following weighted least squares function:

$$J = \sum_{i,j=1}^{V} f(X_{ij})(w_i^T w_j + b_i + b_j - log(X_{ij}))^2$$

where V is the size of the vocabulary (36,726 in our corpus), X is a co-occurrence matrix, w_i and w_j are word vectors for words i and j, and b_i and b_j are bias terms for w_i and w_j. A weighting function f is meant to give not too much weight to very rare and very frequent co-occurrences. It is given as:

$$f(x) = \begin{cases} (x/x_{max})^{\alpha} & \text{if } x < x_{max} \\ 1 & \text{otherwise} \end{cases}$$

GloVe authors recommend setting $\alpha = \frac{3}{4}$ (Pennington et al. 2014) and we follow their suggestion.

In implementing the model, we use TensorFlow on Python, a deep learning package optimized for a NVIDIA GPU. For optimization, the adaptive subgradient algorithm (Duchi et al. 2011) is used.[2] Figure 4 shows the loss over time. The upper pane of Figure 5

[2]This algorithm is available as a function in TensorFlow. The learning rate of 0.05. With NVIDIA Quadro P5000 GPU, the implementation took 11 hours.

shows sample 1,000 words' embeddings whose dimensions are reduced to two by using the T-distributed Stochastic Neighbor Embedding algorithm (van der Maaten and Hinton 2008). The lower pane of Figure 5 shows the south part of the upper pane, in which some words that have similar meanings, such as "overseas" and "foreign," tend to get grouped together. These results suggest that our training methods are working as expected.

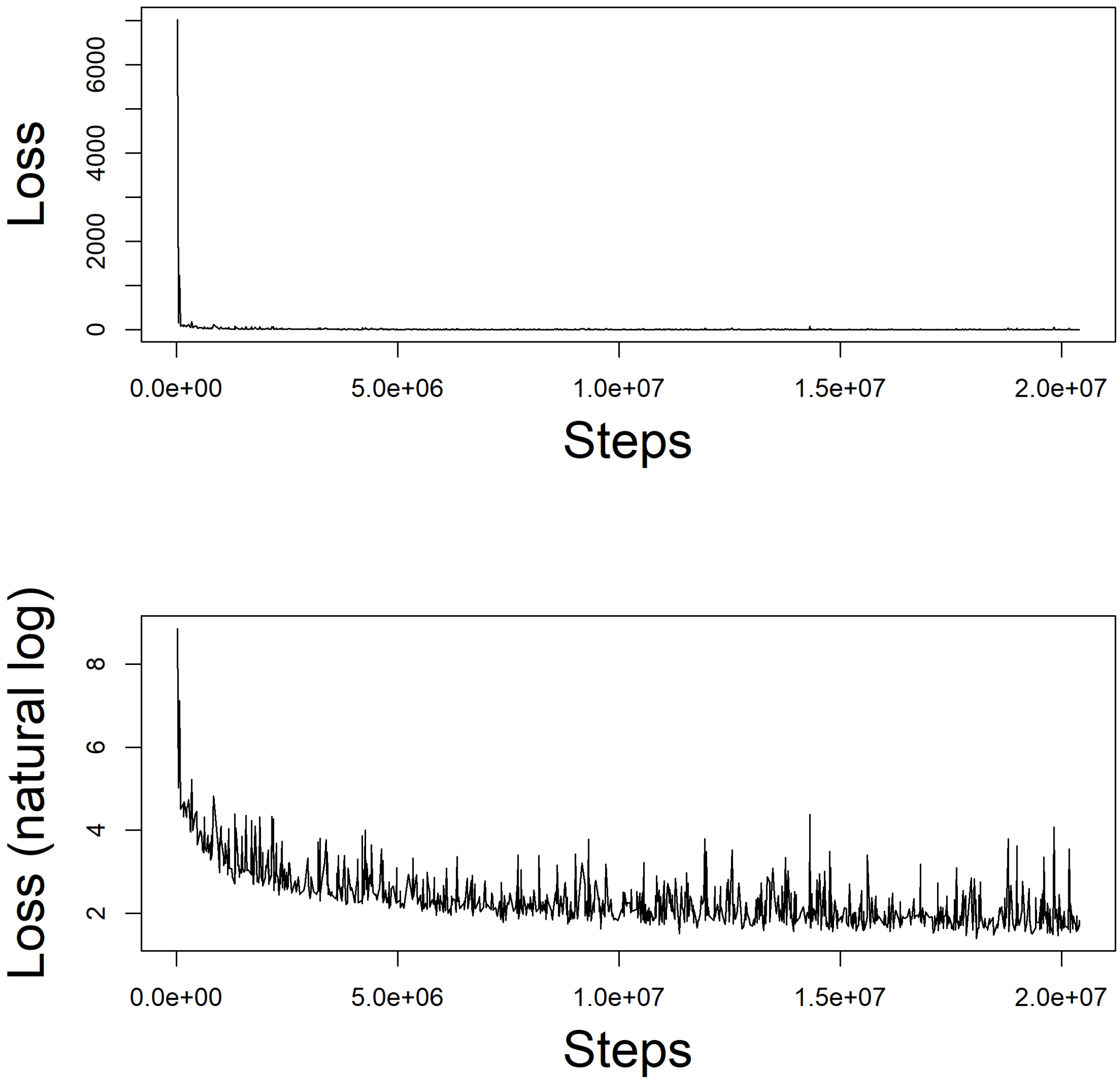


Figure 4: Model Loss and the Number of Steps.
Note: The upper pane shows the absolute values of the loss across time, while the lower pane shows the natural log.

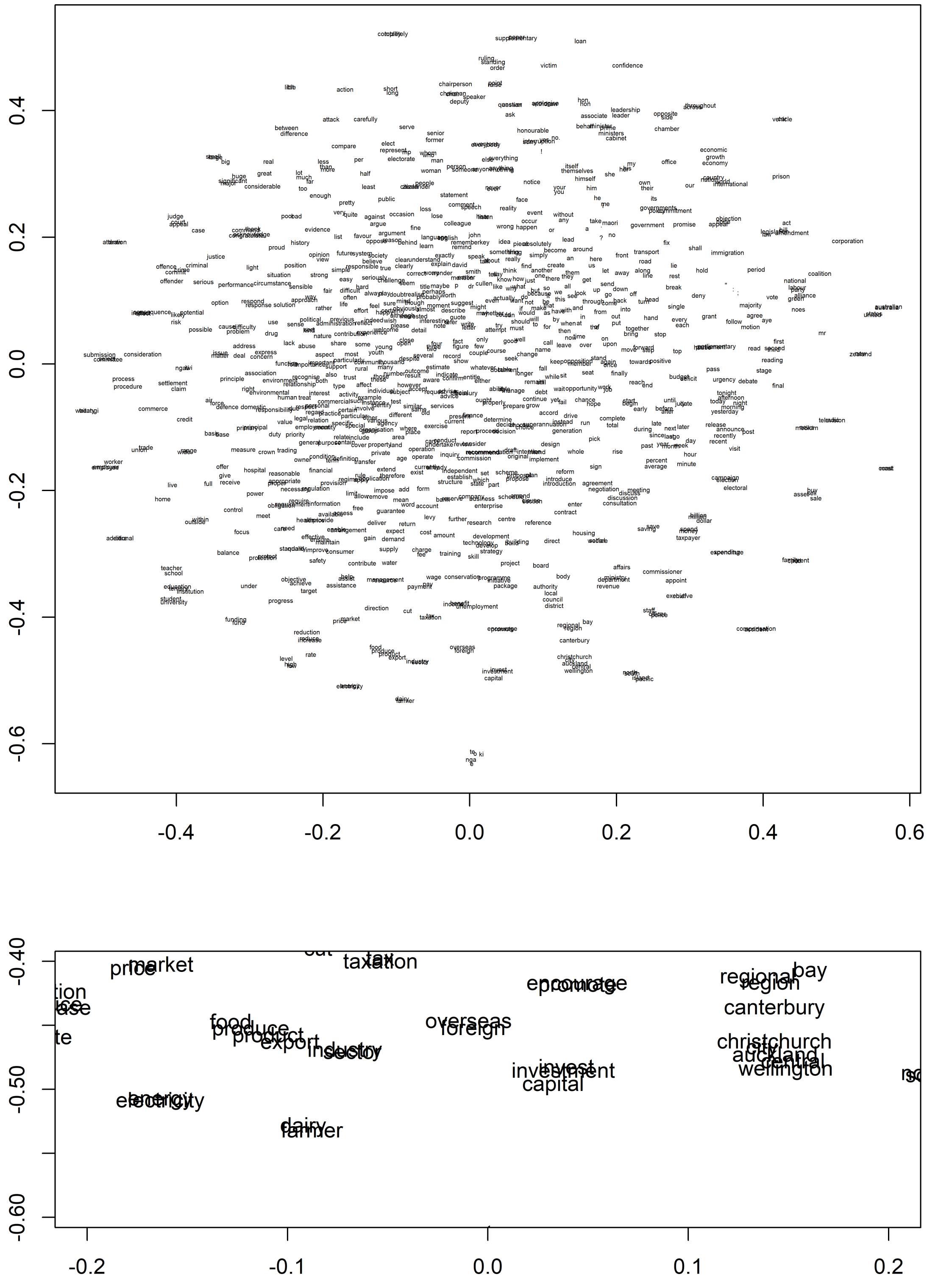


Figure 5: Word Embeddings in Two Dimensions.

Note: The upper pane shows sample 1,000 words' embeddings whose dimensions are reduced to two by using the T-distributed Stochastic Neighbor Embedding algorithm.

The lower pane shows a portion of the upper pane.

3.3 Emolex as Seed Words

Having computed the word vectors, we next turn to the issue of the sentiments associated with each word. Seed words are a set of words that have clear associations with certain sentiment. For instance, commonly used seed words are positive sentiment words such as "brilliant" and "integrity" and negative sentiment words such as "abhor" and "oppression." Using these seed words allows for the estimation of the sentiment of a given word by calculating proximity of the word and seed words.

In contrast to the existing research focusing on seed words representing generic positive and negative sentiment (Rheault et al. 2016), we choose to focus on the emotion of anger. This is because negative feelings can include boredom, sadness, and fear (Ekman 1992; Russel 1980), which do not capture anger and hostility inside a parliament. The emotion of anger is closely related to hostility, such that they are studied as a part of a whole in many areas of medicine (Kemeny and Shestyuk 2008). As Darwin (1862) once put it, the emotion of anger is evoked by dislike and hatred: "If we have suffered or expect to suffer some willful injury from a man, or if he is in any way offensive to us, we dislike him; and dislike easily rises into hatred. . . Few individuals. . . can long reflect about a hated person, without feeling and exhibiting signs of indignation or rage" (p.239). Thus we assume that adversarialism between the ruling and opposition parties inside the parliament can involve offensive and even abusive language, which can be captured by words associated with anger.

There has been no publicly available lexicon on different emotions, except the Emolex developed by Mohammad and Turney (2010; 2013). They use Amazon Mechanical Turk, an online crowd sourcing service, to annotate thousands of commonly used English words in terms of Plutchik's (2001) eight basic emotions: anger, fear, sadness, disgust, surprise, anticipation, trust, and joy. To compute the sentiment, people hired via Amazon Turk are assigned to the task of rating each word in a four-point scale (e.g. "startle is not, weakly, moderately, or strongly associated with joy"). After some post-processing the crowd sourced responses,[3] they list 1,483 words as pertaining to the emotion of anger. Fifty anger words from the Emolex, in order of their intensity (Mohammad and Bravo-Marquez 2017), are shown in Table 1.

1	outraged	11	screwyou	21	fuckoff	31	murder	41	killing
2	brutality	12	murderer	22	rage	32	raging	42	combative
3	hatred	13	fury	23	loathe	33	explosive	43	gofuckyourself
4	hateful	14	execution	24	damnation	34	infuriates	44	vengeance
5	terrorize	15	angered	25	fucktard	35	pissed	45	wrath
6	infuriated	16	savagery	26	homicidal	36	ferocious	46	torment
7	violently	17	slaughtering	27	roadrage	37	obliterated	47	vicious
8	furious	18	veryangry	28	furor	38	rape	48	massacre
9	enraged	19	assassinate	29	hostile	39	vengeful	49	threatening
10	furiously	20	annihilation	30	annihilate	40	sopissed	50	abhorrent

Table 1: Top 50 Anger Words from the Emolex

[3]See Mohammad and Turney (2010; 2013) for detailed procedures.

3.4 Assigning Anger Scores to Words and Speeches

Of the 1,483 anger words from the Emolex, we use the 1,112 words that appeared in the corpus at least ten times as seed words. It is important to note here that a decision to use all the anger words from the Emolex as seed words is not as innocuous as may seem at first glance. Some words in the Emolex are dubiously classified as associated with anger, such as "opera," "trumpet," and "tree." Emolex also contains some words that may be related to anger in certain contexts but may not be considered as such in the context of the New Zealand parliament, such as "warfare," "argue," and "politics." As a robustness check, we opt to use different samples of seed words: i.e. anger words whose intensity is greater than the average and anger words whose intensity is greater than the average plus one standard deviation (Mohammad and Bravo-Marquez 2017). Since the results we find are very similar in both cases, we opt to use all the 1,112 common words as seed words.

Based on the 1,112 seed words, we calculate cosine similarity values between each of the 36,726 unique words in the corpus on the one hand and the 1,112 seed words on the other. An anger score is assigned to each of the 36,726 words, by simply taking the mean of the 1,112 cosine similarity values. The anger scores are rescaled to 0 to 1, with 1 being the greatest anger and 0 being the greatest neutrality. The top sixty anger scores and the top sixty neutral scores are shown in Tables 2 and 3. The results look encouraging and reassuring, in that the list in Table 2 shows considerably offensive/hostile words, while the list in Table 3 looks fairly value-neutral. These lists suggest that our anger score assigning process appears to be valid.

1	perpetuate	1.000	21	inhumane	0.912	41	unwanted	0.886
2	intimidate	0.969	22	patronise	0.907	42	shabby	0.886
3	scaremongering	0.959	23	ravage	0.905	43	humiliation	0.886
4	tactic	0.957	24	alleged	0.905	44	condone	0.886
5	unwarranted	0.945	25	maim	0.904	45	symptom	0.885
6	mindless	0.944	26	downright	0.903	46	malaise	0.885
7	inherently	0.935	27	terrify	0.901	47	misappropriation	0.884
8	racism	0.934	28	exploitative	0.900	48	uncooperative	0.884
9	bitter	0.932	29	shilly-shally	0.899	49	tendency	0.884
10	mayhem	0.930	30	avoidable	0.899	50	cynicism	0.883
11	unfounded	0.929	31	ill-informed	0.898	51	cronyism	0.883
12	horrendous	0.928	32	hypocrisy	0.897	52	abject	0.883
13	divisive	0.927	33	grotesque	0.895	53	smuggling	0.882
14	scurrilous	0.923	34	politicking	0.895	54	confrontation	0.880
15	ugly	0.921	35	prevarication	0.891	55	irrational	0.880
16	insensitive	0.913	36	wilfully	0.890	56	provoke	0.880
17	emotion	0.913	37	grief	0.890	57	unjustified	0.880
18	suffering	0.913	38	ignorance	0.888	58	pomposity	0.879
19	perpetrate	0.913	39	outright	0.888	59	hypocritical	0.879
20	dishonesty	0.912	40	needlessly	0.888	60	duplicitous	0.879

Table 2: Top 60 Anger Words from Hansard

Finally, based on these anger scores for the 36,726 words, we assign anger scores to each

35565	develop	0.122	35585	ensure	0.102	35605	note	0.034
35555	opportunity	0.126	35575	offer	0.115	35595	available	0.091
35556	second	0.125	35576	approve	0.113	35596	thank	0.088
35557	appropriate	0.124	35577	board	0.112	35597	also	0.078
35558	part	0.124	35578	committee	0.111	35598	recommend	0.072
35559	future	0.124	35579	primary	0.111	35599	mention	0.070
35560	expand	0.124	35580	able	0.110	35600	set	0.069
35561	regional	0.123	35581	forward	0.105	35601	development	0.067
35562	consider	0.123	35582	currently	0.103	35602	excellent	0.053
35563	funding	0.122	35583	:	0.102	35603	announce	0.051
35564	proposal	0.122	35584	please	0.102	35604	agree	0.050
35565	develop	0.122	35585	ensure	0.102	35605	note	0.034
35566	important	0.121	35586	first	0.100	35606	addition	0.030
35567	indicate	0.121	35587	discuss	0.100	35607	establishment	0.025
35568	acknowledge	0.120	35588	receive	0.099	35608	include	0.022
35569	confirm	0.120	35589	next	0.099	35609	meet	0.020
35570	te	0.120	35590	refer	0.097	35610	advise	0.014
35571	hon	0.119	35591	congratulate	0.097	35611	enable	0.011
35572	supplementary	0.118	35592	review	0.095	35612	propose	0.010
35573	sure	0.118	35593	table	0.094	35613	establish	0.006

Table 3: Top 60 Neutral Words from Hansard

of the 821,442 speeches. We do this simply by calculating the mean of the anger scores of the words that appear in a given speech. More formally, the anger score of a given speech is given by:

$$\frac{\sum_{i=1}^{n_s} I(w_i \in L)s_i}{\sum_{i=1}^{n_s} I(w_i \in L)}$$

where $w_i(1, ..., n_s)$ denotes a word that appears in a given speech, I an indicator function which equals one if w_i is in the 36,726 words (L), and s_i the anger score of w_i.

We opt to not do any further syntactic analysis to refine the anger scores for speeches at this point, as we believe that the act of speaking more offensive and criticizing words should create significantly more hostility in parliament by itself and thus should represent adversarialism inside the parliament well. We believe that that further refinements could yield further insights in the future.

3.5 Validation

Based on the anger scores assigned to the 821,442 speeches, we now check if we really observe criticizing and offensive speeches where they should appear.

First, it is expected that the Speaker of the House or the Chairperson of a committee should be more neutral. Even though the norm in New Zealand is that Speakers come from the governing party (with a few exceptions), and the Speaker does not sever links with his or her party, still "the Speaker does not play a politically partisan role, and exercises restraint in the speeches or comments he or she makes outside the House. The Speaker must be prepared to assert an independence from the Government to ensure that the rights of all sides of the House are protected in the course of the parliamentary process" (McGee 2017: p.78). One of the Speaker's duties is to "maintain order and decorum in the House" (McGee 2017: p.150). Similarly, Chairpersons of committees of the whole House and select committees play much the same roles as the Speaker of the House (McGee 2017: p.272).

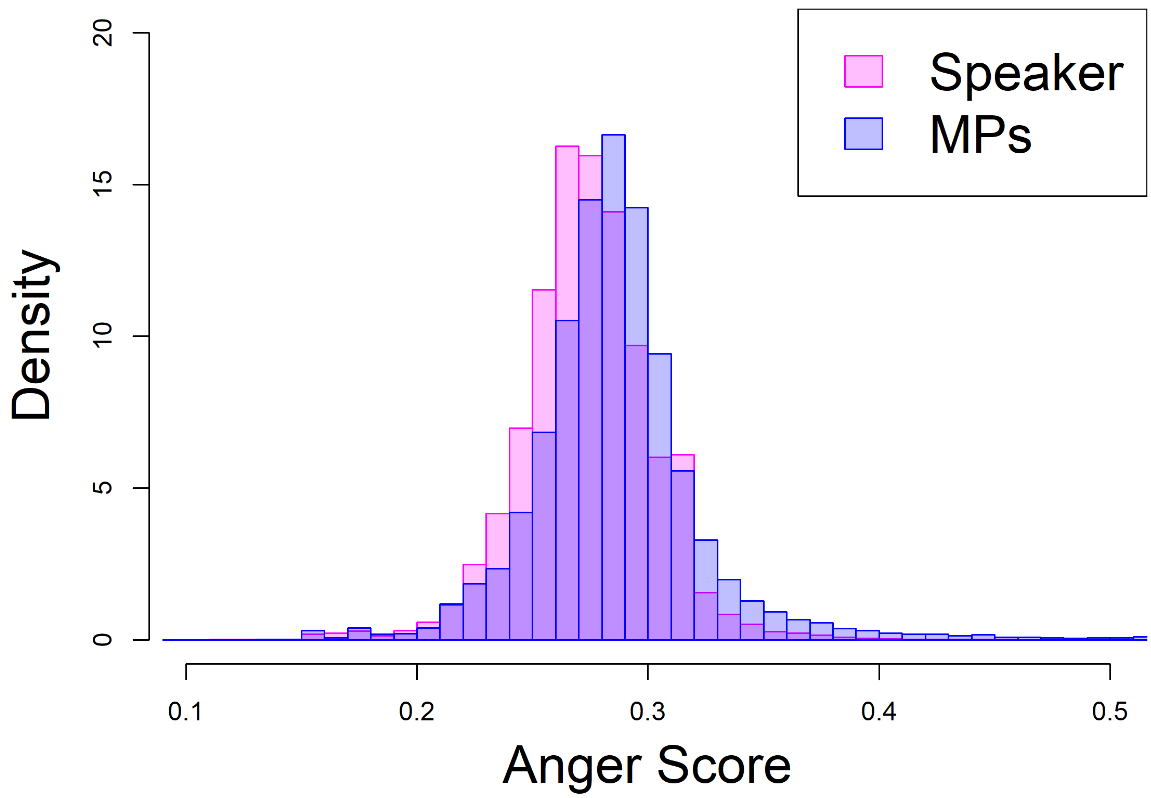


Figure 6: Anger Scores, Speaker/Chairperson versus MPs.

We thus expect that, in playing the roles of arbiters, Speakers and Chairpersons should use less angry language. Figure 6 shows histograms of the anger scores of speeches made by Speakers and Chairpersons and MPs.[4] The graph shows that Speakers and Chairpersons use more neutral language than MPs. Welch's two-sample t-test suggests that two groups' means — 0.274 and 0.287 — are statistically significant at the 99.9 percent level.[5]

Our second method of validating our method comes from the use of Speakers' and Chairpersons' intervention during debates, as Graham (2016) documents. Parliamentary procedures require that Speakers and Chairpersons intervene in debates when members breach

[4]Speakers and Chairpersons include Deputy, Assistant, and Acting Speakers and Chairpersons.
[5]t = -125.94, df = 181,150.

the protocols in several ways. These range from common calls for order to the very rare procedure of naming a member, wherein the offending MP is suspended from the house for gravely breaching the parliamentary norms. In between are Speakers' requests for withdrawal of unparliamentary expressions and apology for having used them (McGee 2017: p.152). We focus on Speakers' and Chairpersons' requests for withdrawal and apology, as calls for order are too frequent and naming is too rare.[6]

To apply this method, we first find topics containing speeches where Speakers or Chairpersons say "withdraw" and "apologise." We assume that such topics should be more hotly debated ones that should contain especially hostile words more often than in other debates. Therefore, we see if peak hostility, as measured by the 95 percentile of anger scores in a given topic, is different between hotly debated topics and others. As Figure 7 shows, topics containing Speakers' and Chairpersons' intervention during debates, or hotly debated topics, are indeed marked by the more hostile tone of MPs than otherwise. Welch's two-sample t-test suggests that two groups' means — 0.345 and 0.314 — are statistically significant at the 99.9 percent level.[7] Thus, Speakers and Chairpersons intervene in what we find especially hostile speeches.

In sum, this section describes the lexicon-based unsupervised classification method to classify words and speeches in the Hansard documents. The results of the word embedding model seem to be working as expected, as similar words tend to get grouped together. As the lists of the words with the top sixty anger scores and the top sixty neutral scores show, the assigned anger scores to words appear to be reasonable. Assigning anger scores to speeches would require more refined approaches such as syntactic analysis, but our simple approach is able to produce fairly sensible results, since we observe criticizing and offensive speeches where they should appear. That is, the tone of the Speaker of the House and the Chairperson of committees tends to be more neutral. This is also corroborated by our finding that more hostile speeches are associated with interventions by Speakers and Chairpersons requesting that MPs withdraw and apologize for their speeches.

4 Hypothesis Testing

With the above data on anger scores, in this section we test the hypothesis that the New Zealand parliament has become collegial and consensual over time. We do this by first looking at overall trends before and after the electoral reform. We also run some simple regression models to estimate anger scores.

[6] Out of the 21,032 topics that we cover, there are 8,999 topics (42.8 percent) in which the Speaker or chairpersons mentioned "order," while the Speaker or chairpersons mentioned naming and suspending an MP in only 172 topics (0.8 percent). The Speaker or chairpersons mentioned withdrawal and apology in 1,457 topics (6.9 percent).

[7] t = 38.132, df = 2,036.8.

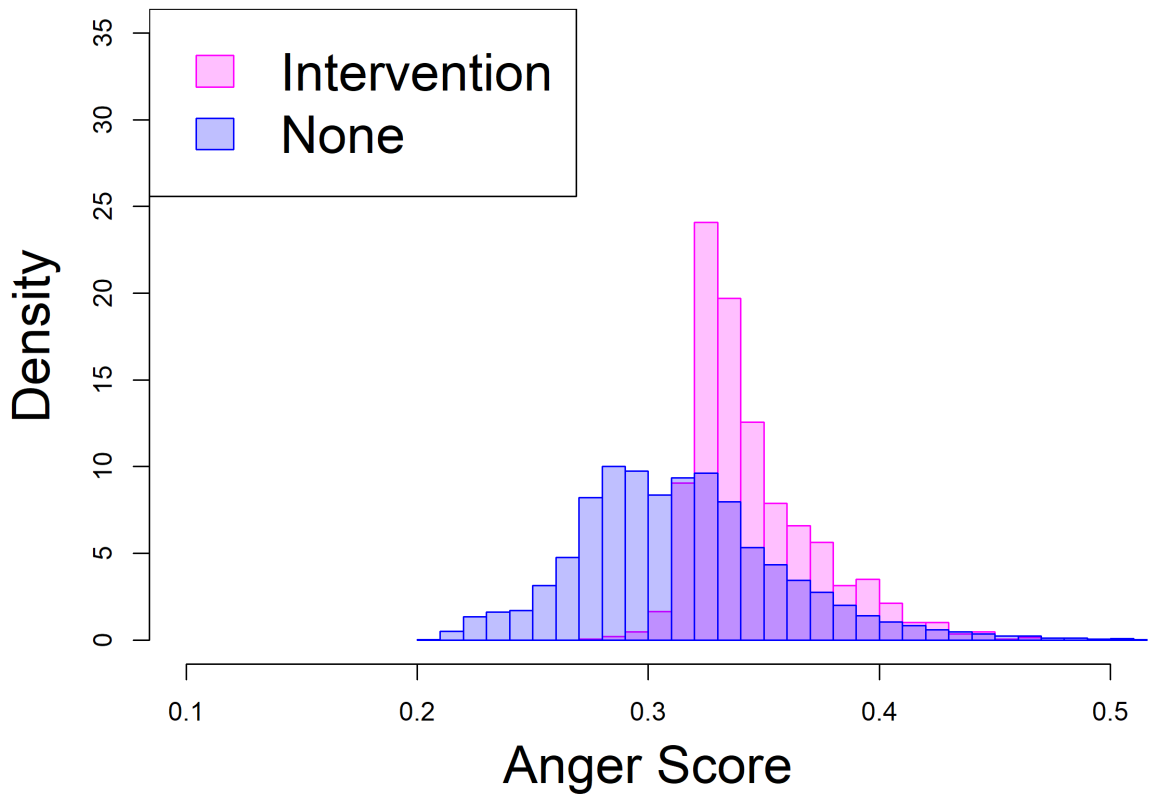


Figure 7: Anger Scores, Aggregated at the Level of Topics, Comparing Topics Containing Speakers'/Chairpersons' Intervention (Calls for "Withdraw" and "Apologise") versus Otherwise.

4.1 Overall Trends

Figure 8 shows the anger scores of speeches made by MPs over time.[8] Note that speeches by the Speakers of the House and the Chairpersons of committees are excluded from the sample, because, as we discuss above, their tones are significantly more neutral than MPs and one of their duties is to prevent MPs from engaging in disorderly behavior and using unparliamentary language. Anger scores are aggregated at the monthly level. We also plot a lowess curve to help observe the trend. The overall trend shown in the figure indicates that, despite some ups and downs, adversarialism inside the New Zealand parliament has decreased over time, which is generally consistent with the theoretical expectation.

Note that the graph also suggests the downward trend might have existed before the observed period, which starts from 1987. Unfortunately, with the data we have now, we are not able to systematically refute this alternative hypothesis. Instead, we offer some more refined data analyses to support our claim.

To do so, we further delve into the overall pattern by looking at who were the main drivers of the moderation of adversarialism inside the parliament. Figure 9 compares the anger scores of speeches made by ruling party members and opposition party members. First, when in opposition, members tend to be more criticizing than when in the government. This is consistent with the general pattern that we show in Figure 10, where we compare the anger scores from the two main parties, Labour and National. Second, the linguistic tone of opposition members did not change much after the reform. In other words, pre- and post-reform opposition members are more or less equally criticizing when speaking up inside the parliament.

Third, most importantly, the tonal change seems to have been driven by ruling party members. Theoretically, it is reasonable that ruling party MPs tend to use more neutral words after the reform. This is because, as explained above, the introduction of MMP to New Zealand brought about the emergence of the multi-party system and, consequently, minority governments. Note that after the reform, all the governments formed in New Zealand were minority governments except the first few years of the 45th Parliament (1996-1999), when National formed a majority coalition government with New Zealand First. As a result, ruling parties should be more accommodative to opposition parties' policy demands and their speaking styles should become less offensive.

Figure 10 compares the anger scores of speeches made by MPs from the two major parties, or Labour and National. Note that Labour was in the government between 1987 and 1990 and 1999 and 2008, while National was in power between 1990 and 1999 and 2008 and 2016. The graph shows that, regardless of their partisan affiliations, members from the two major parties tend to get more moderate when in the government than when in the opposition. In addition, post-reform Labour members in the government (i.e. Labour between 1999 and 2008) were more neutral than pre-reform Labour members in the government (i.e. Labour between 1987 and 1990).[9] Similarly, post-reform National members in the government (i.e. National

[8]The noticeable outlier in this figure stems from a single parliamentary meeting that took place in January 1991, when the Prime Minister gave an address on the invasion of Iraq, using an unusual amount of hostile words.

[9]The average score of pre-reform Labour members' speeches is 0.3053, while that of post-reform Labour members' speeches is 0.3003. The difference is statistically different at the 99.9% level, with t = 19.851 and

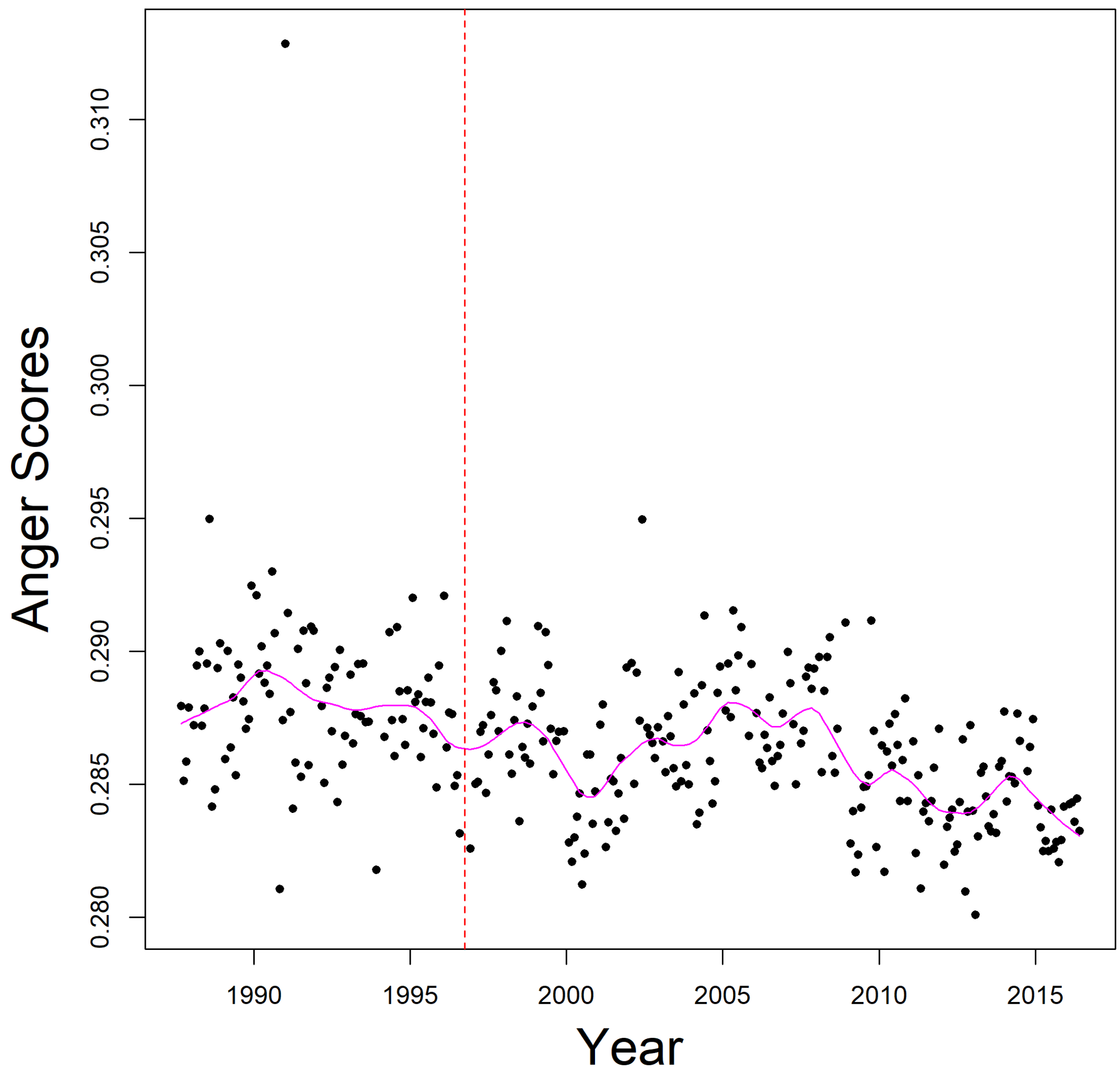


Figure 8: Anger Scores Aggregated at the Monthly Level.
Note: The red dash line indicates the month of the first MMP election.
The purple solid line indicates the lowess curve.

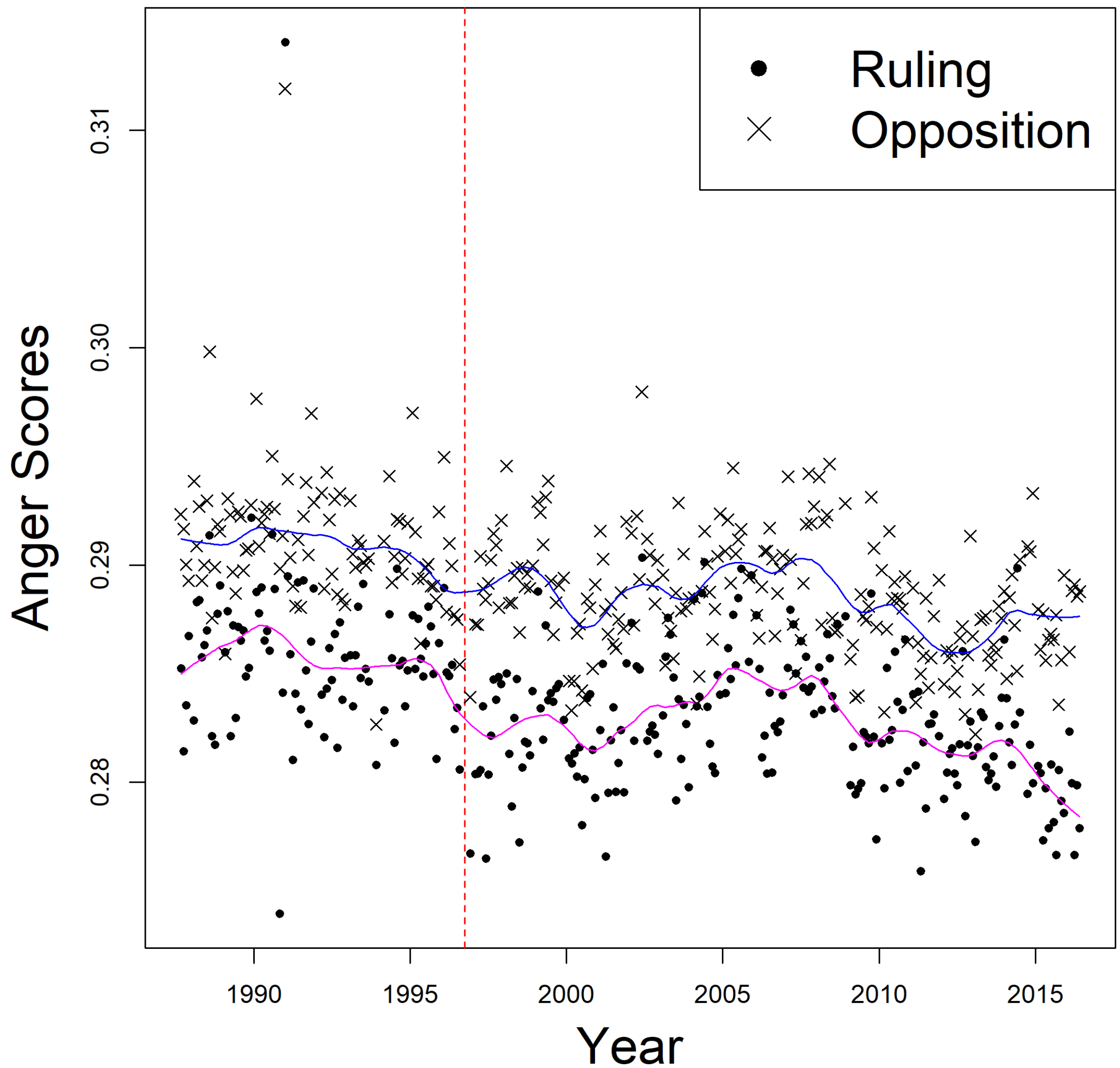


Figure 9: Anger Scores Aggregated at the Monthly Level.
Note: The red dash line indicates the month of the first MMP election.
The purple solid line indicates the lowess curve for ruling party members.
The blue solid line indicates the lowess curve for opposition party members.

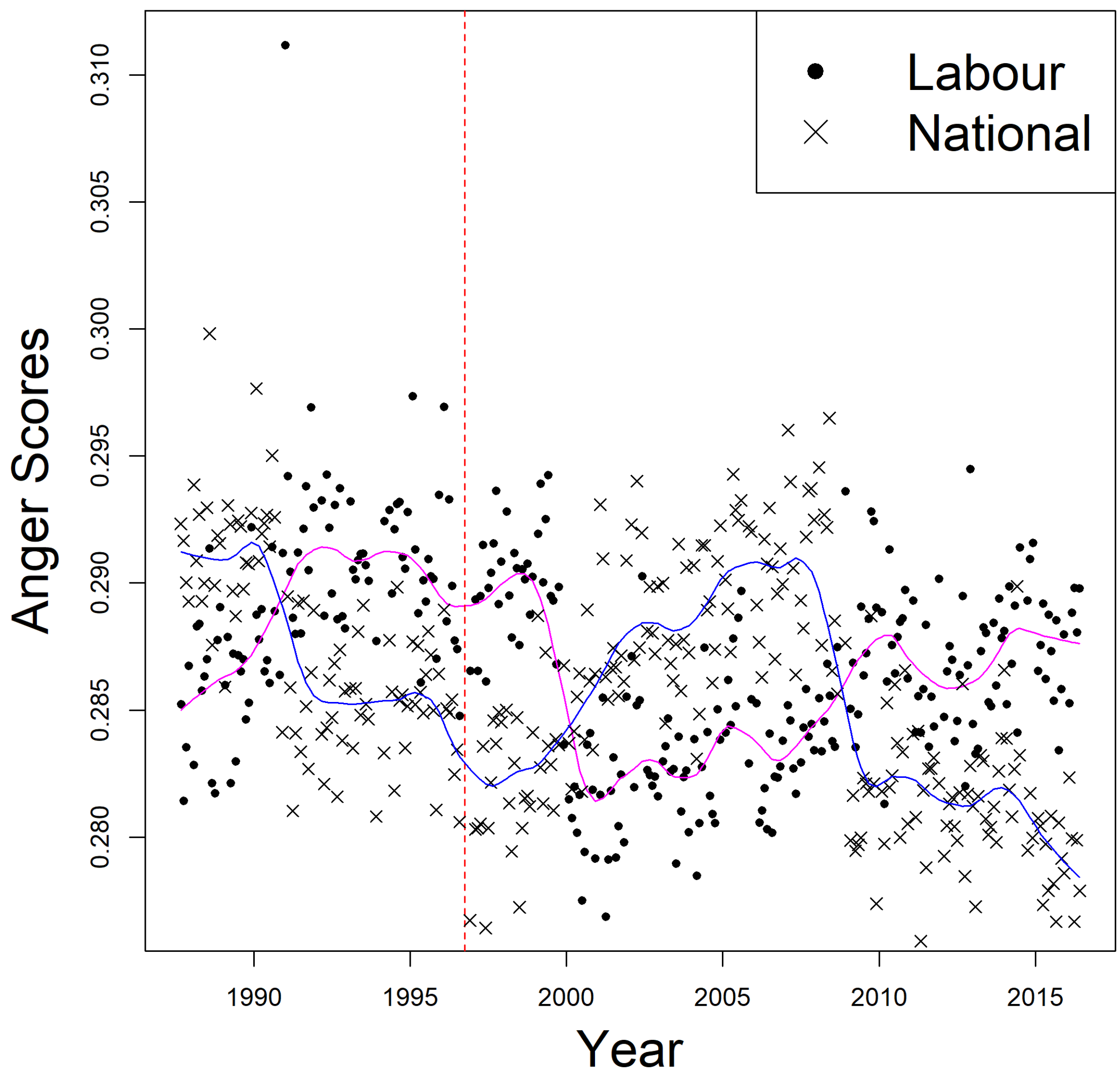


Figure 10: Anger Scores Aggregated at the Monthly Level, Labour Party Members versus National Party Members.

Note: The red dash line indicates the month of the first MMP election.
The purple solid line indicates the lowess curve for Labour.
The blue solid line indicates the lowess curve for National.

between 1996 and 1999 and 2008 and 2016) tended to use less offensive words than pre-reform National members in the government (i.e. National between 1990 and 1996).[10]

One alternative explanation that might explain this decline in hostility is that MPs were replaced over time due to the reform. That is, parties might have started recruiting new types of candidates who happened to speak moderately inside the parliament. This could have happened by coincidence due to unrelated reasons, which would work against our intuitional change hypothesis, or deliberately, as a consequence of the reform. In the former case, we would expect to see new MPs speeches to be less hostile, but not existing MPs. In the latter case, we would expect both types of MPs to become less hostile.

To investigate this possibility, we differentiate the sample of MPs into three cohorts: (1) those who survived the reform; (2) those who terminated their political career before the reform; and (3) those who were first elected to the parliament after the reform. Figure 11 compares these three different cohorts. First, there is a significant difference between the pre- and post-reform cohorts.[11] Second, those who experienced in the middle of their political career the switch to the new system changed their tones inside the parliament.[12] Given that both types of MPs see a reduction in hostility, these two patterns combined suggest that the institutional reform more likely caused this change.

Finally, we investigate whether MPs tried to avoid very hostile words after the reform. If that is the case, then the peak of anger scores should go down more rapidly than the median. To see if peak hostility has fallen post-reform, we calculate the 90 and 95 percentiles of anger speeches on a monthly basis and compare them to the median anger, as shown in Figure 12. Both percentile measures seem to show a decrease post-reform, and the decrease appears to be faster than the median, especially the 95 percentile. This suggests that MPs after the reform gradually tried to refrain from using very hostile words in the parliament.

To formalize the perceived breaks we see in the graphs, we conduct several tests on our measures of peak hostility. We first conduct the standard Augmented Dickey-Fuller and Phillip-Perron tests of unit roots for both measures at the quarterly level,[13] with and without a linear trend, and reject the hypothesis of a unit root in all cases. For the 95 percentile, Wald tests reject the hypothesis of no structural break at 1% significance and find the most likely candidate for a break to be quarter 2 of 1996 (with no linear trend) and quarter 4 of 1993 (with a linear trend); for the latter a Wald test rejects the hypothesis of no break in quarter 2 of 1996 at 1% significance level. Equivalent tests at the 90 percentile also reject the hypothesis of no break at 1% significance, with the most likely candidate dates being quarter 4 of 2001 (with no linear trend) and quarter 1 of 1996 (with linear trend); for the former, we also do not reject the hypothesis of a break in quarter 1 or 2 of 1996, albeit at

df = 84,215.

[10]The average score of pre-reform National members' speeches is 0.3030, while that of post-reform National members' speeches is 0.2992. The difference is statistically different at the 99.9% level, with t = 20.029 and df = 159,000.

[11]The average score of the pre-reform cohort's speeches is 0.3059, while that of the post-reform cohort's speeches is 0.3043. The difference is statistically different at the 99.9% level, with t = 9.204 and df = 106,810.

[12]The average score of the pre-reform cohort's speeches is 0.3059, while that of the post-reform cohort's speeches is 0.3025. The difference is statistically different at the 99.9% level, with t = 24.793 and df = 297,510.

[13]The time-series tests we use require data without gaps, which is true at a quarterly, but not monthly, level.

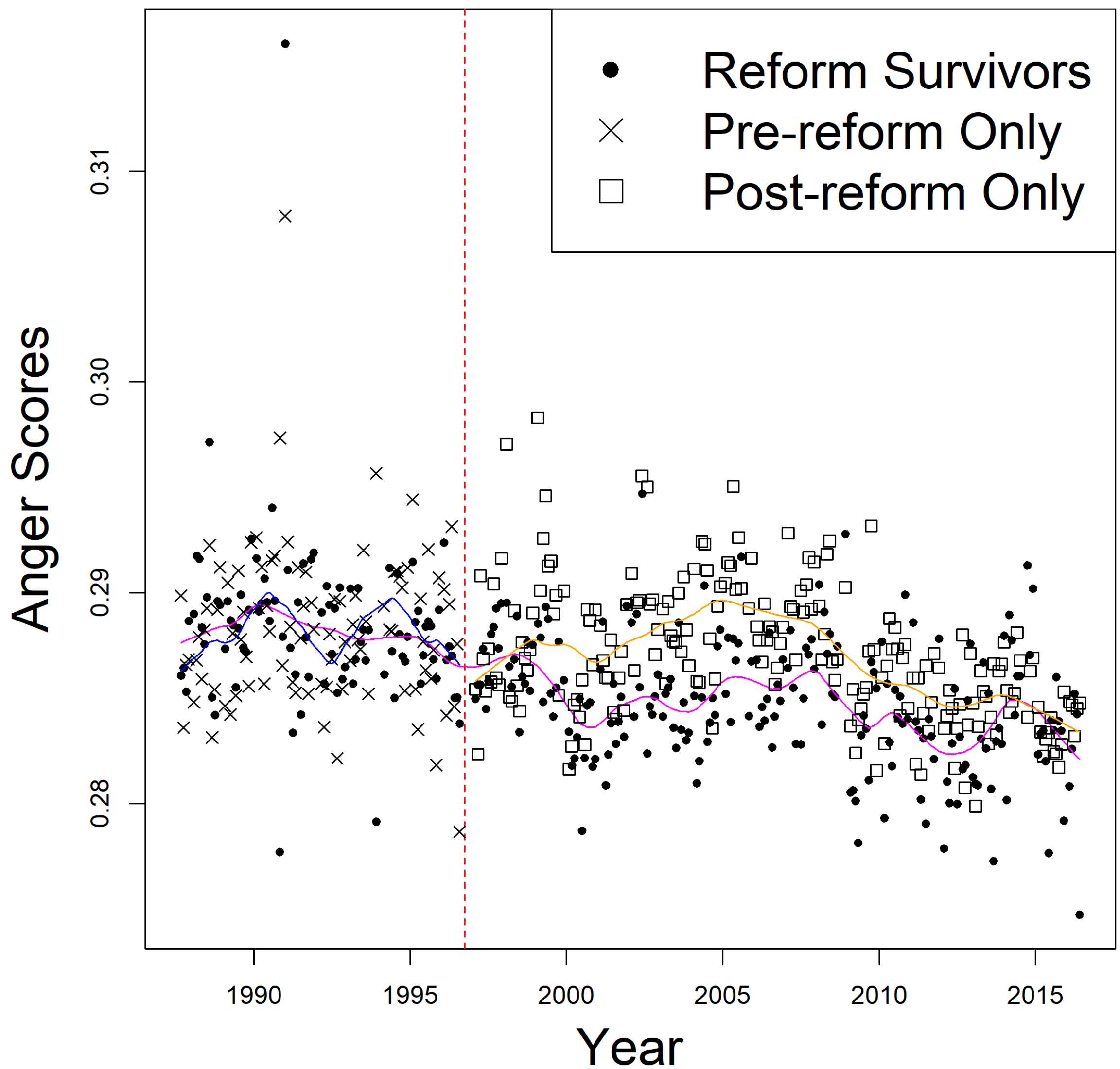


Figure 11: Anger Scores Aggregated at the Monthly Level, Large Party Members versus Small Party Members.
Note: The red dash line indicates the month of the first MMP election.
The purple solid line indicates the lowess curve for large parties (Labour and National).
The blue solid line indicates the lowess curve for small parties (ACT, Alliance, Green, Mana, Maori, New Labour, New Zealand First, Progressive, and United).

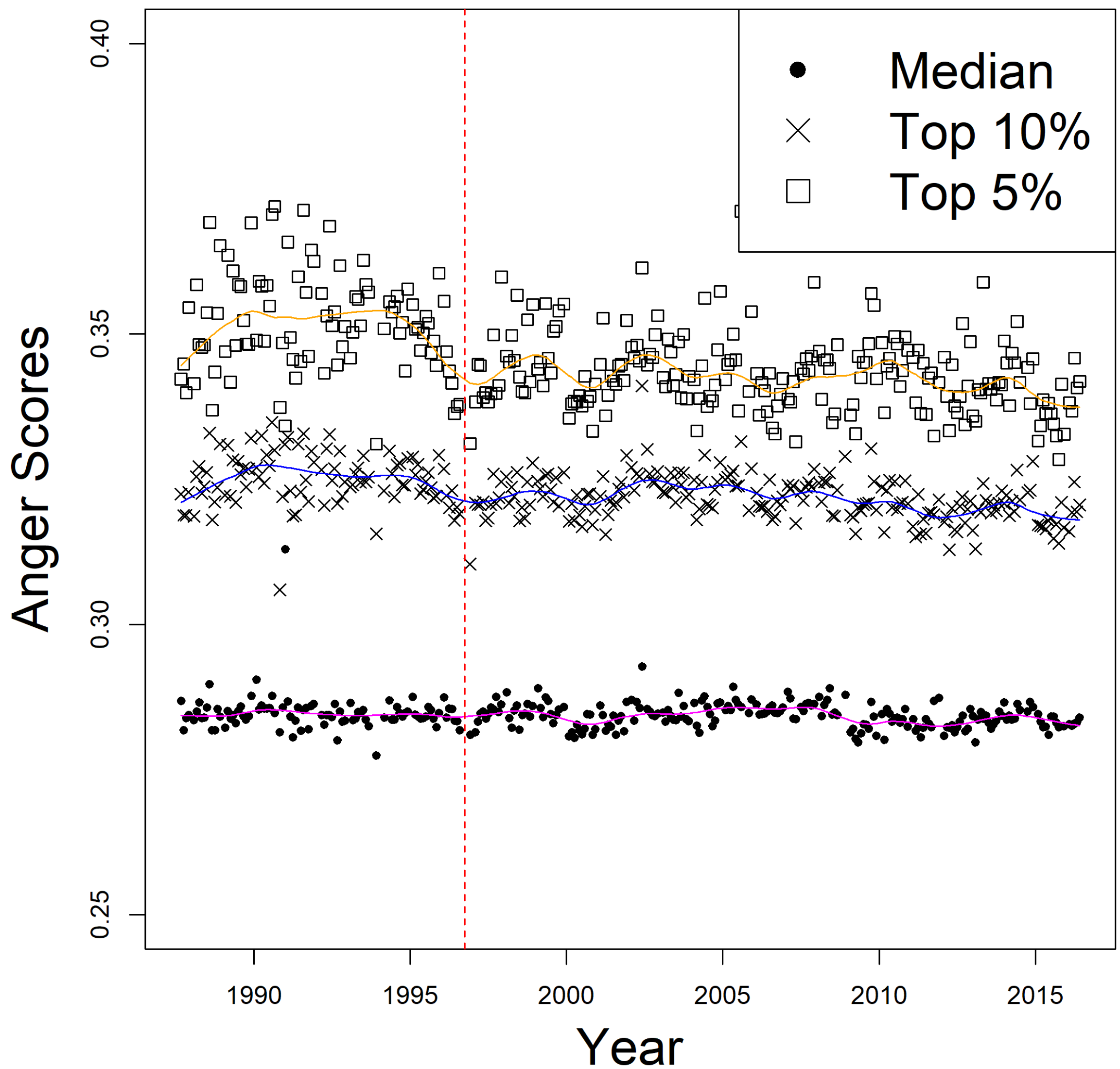


Figure 12: Anger Scores Aggregated at the Monthly Level, Median and 90 and 95 Percentiles.

Note: The red dash line indicates the month of the first MMP election.
The purple solid line indicates the lowess curve for the median of anger scores.
The blue solid line indicates the lowess curve for the 90 percentile of anger scores.
The orange solid line indicates the lowess curve for the 95 percentile of anger scores.

5% significance. These combined results are evidence that the reform likely affected peak hostility, given the suggestive evidence of a break around the time of the first election with MMP.

In sum, this subsection looks at overall trends in speeches' anger scores. Our data are confirmatory with the view that the level of hostility has gone down in the New Zealand parliament since the electoral reform. The decrease appears to be caused by ruling parties, regardless of partisanship. Our data also suggest that the decline in the level of hostility seems to have been caused by the adaptation of MPs to the new institutional environment, not by replacements, and that MPs have tried to avoid very hostile words after the reform.

4.2 Regression Analysis

In this subsection we further test our hypotheses using panel regressions. Our first analysis simply compares the levels of verbal aggressiveness before and after the reform by using a couple of samples.[14] The first sample covers anger scores aggregated at the level of 21,032 topics. In aggregating anger scores, we simply take the average and 95 percentile of anger scores of the speeches that a given MP made for a given topic. Thus the observation unit for the first sample is MP-topic. We construct our second sample by aggregating at the level of 2,203 parliamentary meetings, using the same approach. The size of the first sample is 182,494 MP-topics and 108,086 MP-days in the second.

In order to test our hypothesis that post-reform MPs, in particular ruling party MPs, use less hostile words, we use three key important variables. The first one is Post-reform, which is a dummy variable coded 1 if a speech is made in the post-reform period. Ruling MP is a dummy variable equal 1 if a speech is made by a ruling party member. The interactive term between Post-reform and Ruling MP is also included.

Covariates include the economic atmosphere in New Zealand, since recessions could be associated with heated parliamentary debates. Business Confidence is based on a monthly business outlook survey conducted by ANZ, which asks New Zealand firms whether their business conditions improved, remained the same, or deteriorated.[15] We take the net index, i.e., the percentage of firms answering "improved" minus firms answering "deteriorated."

We also take into account parties' and MPs' electoral concerns. Parties might use hostile language as the next election approaches, so that they can get attention from the media and voters. Therefore we include in our models Electoral Cycle, coded as how many months left until the subsequent rounds of elections. In addition, individual MPs, especially electorally vulnerable ones, might have the similar incentive. Thus our models also include Margin, an MP's vote margin with the best loser. Note that in the post-reform period, a candidate can be dually nominated on both of the nominal and list components, which means that a candidate losing on a single-member district can win a seat through the list. For these MPs, Margin is measured as their vote margin with the district winner and takes the negative values. Also

[14] We use aggregated measures for speeches, partly because anger scores at the speech level vary highly by construction: they will irregularly jump up when an MP says only one hostile word, such as "Insensible!", while long speeches tend to dilute the anger score. Thus aggregation can smooth out speech-by-speech fluctuations in our anger scores and reduce noise. But, although not shown here, the results are much the same when we use each speech as the observation unit.

[15] Available at https://www.anz.co.nz/about-us/economic-markets-research/business-outlook/

note that the analysis excludes those who did not run on the nominal component, as Margin cannot be computed for such MPs.[16]

We need to offset the unobservable characteristics and personalities of individual MPs, such as eloquence, short temper, and richness in vocabulary, since these unobservable characteristics should affect how MPs make speeches. Unfortunately, there is no readily available data on individual New Zealand MPs' personalities.[17] Addressing this potential problem requires the inclusion of MP-fixed effects in the models. We also report standard errors clustered on each MP, since we expect speeches by the same MP to be more or less similar and, as a result, the errors should be correlated within the same MP.

The results are reported in Table 4. The table suggests that, although the levels of significance fluctuate depending on how we construct the samples, these results are consistent with our theoretical expectations. First, the coefficient for Post-reform in the models without the interaction (1, 3, 5, and 7) tends to be negative, suggesting that MPs after the reform are associated with more neutral language in the parliament. Although not robust across the different specifications, this association is consistent with the hypothesis that the introduction of MMP has made the New Zealand democracy more consensual.

Second, the coefficient for Ruling MPs is significantly negative across the models, meaning that ruling party MPs are more neutral than opposition party MPs, as we have seen in the overall trends subsection above. This is reasonable, because the opposition should use harsher language to keep the government accountable.

Third, the interactive term between Post-reform and Ruling MP is negative and significant. This is consistent with our view that, with the introduction of MMP and the rise of multipartyism in New Zealand, minority governments have become the norm and the government after the reform should have become more accommodative to the opposition's policy demands. In addition, the size of the coefficient is twice larger in the models 6 and 8, in which the dependent variable is 95 percentile anger scores. This suggests that the moderation of speeches appears to be largely driven by ruling party MPs' less use of extremely hostile language.

Other variables that are worth mentioning are Electoral Cycle and Margin. Electoral Cycle is negative and significant across the models, meaning that speeches become hostile over time as the subsequent election approaches. Meanwhile, individual MPs' electoral vulnerability does not seem to matter at all, since Margin is not significant in any of the models. We interpret these results combined as meaning that parties appear to strategically criticize the opponent before the elections in order to get media attention, while individual MPs work rather as faceless troops in highly disciplined parties in New Zealand.

Given this finding that ruling party MPs tend to use less hostile language after the reform, we further investigate this mechanism in the second analysis. As stated previously, we expect that, when speaking to small parties, MPs, especially those from governing parties, should try to avoid hostile language, since the government does not want to jeopardize its relationship with potential legislative partners.

Thus we need to define the direction of a given speech and do so by focusing on three

[16] Although not shown here, the results including and excluding list-only MPs are quite similar.

[17] Ramey et al. (Forthcoming) apply machine learning to measure politicians' personality traits, such as Openness, Conscientiousness, and Extraversion, using speeches in the parliament.

	Observation: MP-topic		Observation: MP-day		Observation: MP-topic		Observation: MP-day	
	Dependent Variable: Mean Anger Score				Dependent Variable: 95 Percentile Anger Score			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-reform	-0.0012*	0.0001	-0.0014**	-0.0001	0.0001	0.0028**	-0.0044***	-0.0017
	(0.0007)	(0.0009)	(0.0007)	(0.0008)	(0.0012)	(0.0013)	(0.0015)	(0.0016)
Post-reform ×		-0.0028***		-0.0026**		-0.0055***		-0.0054***
Ruling MP		(0.001)		(0.001)		(0.0015)		(0.0017)
Ruling MP	-0.0068***	-0.0052***	-0.0071***	-0.0056***	-0.0076***	-0.0044***	-0.0086***	-0.0053***
	(0.0007)	(0.0008)	(0.0006)	(0.0008)	(0.001)	(0.0012)	(0.0009)	(0.0014)
Business	-0.0009*	-0.0009*	-0.0004	-0.0004	-0.0007	-0.0007	0.0007	0.0007
Confidence	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Electoral	-0.00004***	-0.00004***	-0.00004***	-0.00004***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
Cycle	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Margin	-0.0013	-0.0011	-0.0011	-0.001	0.0014	0.0018	0.002	0.0023
	(0.0022)	(0.0022)	(0.0019)	(0.0019)	(0.0036)	(0.0035)	(0.0042)	(0.0041)
Observations	182,494	182,494	108,086	108,086	182,494	182,494	108,086	108,086
Adjusted R2	0.004	0.005	0.007	0.007	0.002	0.003	0.003	0.004

Table 4: Fixed-effects Panel Estimations of Anger Scores at Topic and Daily Levels.
Note: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Each model includes MP-fixed effects. Standard errors clustered on each MP in the parentheses.

consecutive speeches, or a triplet of speeches. If a given triplet can be represented as YXY, or if member X's speech immediately follows and is immediately followed by the same member Y's speeches, then we assume that X's speech is meant to be directed towards Y.[18]

With this definition of a speech direction, we conduct panel regressions like the first analysis, but this time the observation unit is each speech. Excluded from our sample are speeches directed towards the Speaker, as well as speeches whose immediately previous and immediately subsequent speeches are made by different speakers. This sample contains 456,512 speeches.

The dependent and independent variables are much the same as in the first analysis: we regress the anger score of a given speech on a series of dummy variables, Post-reform, Ruling MP, and their interactive term. To these we add one more dummy, Speaking to Small Party, which captures whether a given speech is meant to be directed towards a member from a small party or an independent.[19] As we expect government does not want to create animosity towards small party members, we also include three-way interactions between Speaking to Small Party and Post-reform and Ruling MP. We use the same covariates as in the first analysis: Business Confidence, Electoral Cycle, and Margin. In addition, we also include in the second analysis the anger score of an immediately previous speech. We expect that when an MP hears some hostile remarks, he or she is likely to respond to them with more or less similarly hostile speeches. As this is a similar panel setting as the first analysis, we include MP-fixed effects in the models, with standard errors clustered on each MP.

The results are reported in Table 5. The model (1) is a baseline model, while the model

[18] We also use a more simple measure focusing on only a pair of speeches: When member X's speech is immediately followed by member Y's speeches, then X's speech is assumed to be directed towards Y. This methodology, if simple, unfortunately may not work well when one MP's speech is interrupted by the Speaker's intervention or other MPs' random, irrelevant comments. Despite this drawback, the results do not significantly differ when we use this alternative definition.

[19] Small parties include: ACT, Alliance, Green, Progressive, Mana, Maori, New Zealand First, New Labour, and United or United Future.

(2) includes interactions between the variables of our interest. First of all, when a previous speech is more hostile, MPs on average reply with more hostile speeches. This implies that our definition of a speech direction seems to be valid.

Second, the results do not significantly differ from the ones reported in Table 4. That is, consistent with the first hypothesis, ruling party members after the reform tend to use less hostile language in the parliament.

Third and most importantly, as the three-way interactive term in the model (2) indicates, the effects appear to be conditional on speech directions. When post-reform ruling party members' speeches are directed towards a small party member, their anger score is lower than when they speak to a large party member. Such relationship does not seem to have existed before the reform, since ruling party members tended to use harsher words when they speak to a small party member. We interpret these as evidence supporting our proposition: when speaking to small parties, MPs from the government should try to avoid hostile language, as the government almost always lacks a majority now and requires confidence and legislative support from small parties.

	Dependent Variable:	Mean Anger Score
VARIABLES	(1)	(2)
Post-reform	0.0006	0.0005
	(0.0006)	(0.0006)
Postreform × Ruling MP	-0.0043***	-0.0038***
	(0.0011)	(0.0011)
Ruling MP	-0.0053***	-0.0056***
	(0.0009)	(0.0009)
Speaking to Small Party	0.0004	-0.0019
	(0.0003)	(0.0016)
Post-reform × Speaking to Small Party		0.0027
		(0.0017)
Ruling MP × Speaking to Small Party		0.0068***
		(0.0021)
Post-reform × Ruling MP × Speaking to Small Party		-0.0080***
		(0.0021)
Business Confidence	-0.0004	-0.0005
	(0.0004)	(0.0004)
Electoral Cycle	-0.00005***	-0.00005***
	(0.00001)	(0.00001)
Margin	-0.0016	-0.0013
	(0.0025)	(0.0025)
Previous Speaker's Anger	0.1092***	0.1092***
	(0.0037)	(0.0037)
Observations	456,512	456,512
Adjusted R2	0.0172	0.0173

Table 5: Fixed-effects Panel Estimations of Anger Scores at Speech Levels.
Note: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Each model includes MP-fixed effects.
Standard errors clustered on each MP in the parentheses.

In sum, our regression results suggest that, in line with our theoretical predictions, the decline in the level of hostility appears to be associated with the electoral reform. MPs after the reform, especially those from ruling parties, tend to speak less hostile words in the parliament. In particular, this change seems to be driven by ruling party MPs' less and less use of extremely hostile words in the parliament and, to some extent, towards potential future allies, i.e., small parties. This finding seems to be robust with the inclusion of the MP-fixed effects to capture their unobserved individual characteristics.

5 Conclusion

This paper analyzed the impact of a change from a majoritarian democracy to a consensual democracy on adversarialism inside the parliament. Focusing on the case of New Zealand, where MMP was put in use from the 1996 election, we employ a lexicon-based, unsupervised sentiment analysis approach to measure the level of anger of all the parliamentary speeches from 1987 to 2016. We find that the level of anger in the New Zealand parliament has decreased over time. In particular, ruling party members tend to use more neutral words after the reform.

These results suggest that we should find similar and differing levels of hostility in countries using different political systems. For example, we would assume that majoritarian models of democracies, such as the UK, Canada, and the US, should have the higher levels of hostility in their parliaments than in consensual models of democracies as found in Scandinavia. It is also expected that the electoral reform in Italy and Japan in the 1990s should affect the way their parliaments operate. As these countries newly introduced single-member district systems, the level of hostility between two large camps might have gone up.

Furthermore, there is a current debate about polarization in political systems and the undesirable consequences this has, both in politics and for society as a whole (McCarty et al. 2016). Our results suggest that it might be possible to mitigate some of these concerns via electoral reform towards proportional systems. If society is concerned about increasing hostility and has the goal to increase the collegiality of politicians, then these types of reforms are likely to have this positive effect.

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